Optimization of CNC End Milling using Hybrid Taguchi Method using Principal Components Analysis and Utility Theory

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***Abstract* – In order to improve the quality and productivity the present study highlights the optimization of CNC end milling process parameters to provide a good surface finish. Surface finish has been identified as one of the main quality attributes and is directly related to the productivity of a machine. In this paper an attempt has been made to optimize the process such that the best surface roughness value can be obtained in a process. Hence a multi objective optimization problem has been obtained which can be solved by the hybrid Taguchi method comprising of principal components analysis as well as by utility theory. In this work, Individual response correlation has been eliminated first by mean of Principal Component Analysis (PCA) to meet the basic assumption of Taguchi method. Correlated responses have been transformed into uncorrelated quality indices called as principal components. Quality loss estimates have been calculated from the principal components and the utility values are found out for the same. Then the overall utility index has been calculated. Finally, Taguchi method has been used to solve the optimization problem.**

Keywords – CNC Milling, Principal components analysis, Taguchi method, Utility theory

I. INTRODUCTION

In this research the various surface roughness measurements of the product prepared by CNC end milling operationare to be studied experimentally and the results will be interpreted analytically. Quality and productivity are two of the most important criteria in any machining operation. But it can be seen that as the quality increases the productivity tends to decrease. It is therefore essential to optimize quality and productivity simultaneously. In this case we are only considering the different surface roughness parameters. The product being machined has to have the minimum surface roughness, and in order to obtain high quality the processing time has to be compromised which directly affects the productivity. Thus it is very important to optimize both the factors simultaneously.

The interdependence and correlation among quality and productivity is very complex and difficult to understand. In most of the cases the optimization is based on a single objective function. In certain cases it has proven to be effective but in most cases it has adverse effects. Therefore multiple objectives have to be optimized simultaneously.

In end milling surface finish is one of the most important aspects. There are many roughness parameters and Ra is the most commonly used. Other common parameters include Rq, Rz, and Rsk. Some parameters are used within certain industries or within certain countries.

Yang and Chen (2001) demonstrated a systematic procedure of using Taguchi parameter design in process control of individual milling machines. The Taguchi parameter design was carried out in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in an end-milling operation. Ghani *et al.* (2004) applied Taguchi optimization methodology to optimize cutting parameters in end milling while machining hardened steel with TiN coated carbide insert tool under semi-finishing and finishing conditions of high speed cutting considering the milling parameters - cutting speed, feed rate and depth of cut. Oktem *et al.* (2005) focused on the development of an effective methodology to determine the optimum cutting conditions,helping to achieve minimum surface roughness in milling of mould surfaces by coupling Response Surface Methodology (RSM) with a developed genetic algorithm (GA).

The present research proposes the application of Principal Component Analysis (PCA) coupled with Taguchi method to solve such correlated multi-attribute optimization of CNC end milling operation. Principal Component Analysis has been recommended to eliminate correlation between the responses and to estimate uncorrelated quality indices called principal components; Datta et al. (2009a). The quality index (principal component) having the highest accountability proportion has been treated as equivalent single objective function, which has been finally optimized by Taguchi method.

II. PRINCIPAL COMPONENTS ANALYSIS

Principal Component Analysis (PCA) is a way of identifying patterns in the correlated data, and expressing the data in a way so as to highlight their similarities and differences, Johnson and Wichern (2002). The main benefit of PCA is that, the data can be compressed once the patterns in data have been identified, i.e. by reducing the number of dimensions, without much loss of information. The various PCA methods are discussed below:

Assuming, the number of experimental runs in Taguchi's OA design is*m* , and the number of quality characteristics is *n* . The Experimental results can be expressed by the following series: $X_1, X_2, X_3, \ldots \ldots X_i \ldots, X_m$

Here,

$X_1 = \{X_1(1), X_1(2) \ldots \ldots X_1(k) \ldots . X_1(n)\}$

.

.

$X_i = \{X_i(1), X_i(2) \ldots \ldots X_i(k) \ldots X_i(n)\}$

.

.

$X_m = \{X_m(1), X_m(2) \ldots \ldots X_m(k) \ldots . X_m(n)\}$

Here,$X_i$represents the i^{th}experimental results and is called the comparative sequence in grey relational analysis.

Let,X_0be the reference sequence:

Let, $X_0 = \{X_0(1), X_0(2) \ldots \ldots X_0(k) \ldots . X_0(n)\}$

The value of the elements in the reference sequence means the optimal value of the corresponding quality characteristic. X_0 and $X_i$both includes *n* elements, and $X_0(k)$ and $X_i(k)$represent the numeric value of k^{th}element in the reference sequence andthe comparative sequence, respectively, k =1,2,........,n . The following illustrates the proposed parameter optimizationprocesses in detail, (Su and Tong, 1997).

Step 1: Normalization of the responses (Quality Characteristics)

When the range of the series is too large or the optimal value of a quality characteristic is too huge, it will cause theinfluence of some factors to be overlooked. The original experimental data must be normalized to eliminate such an effect. There arethree types of data normalization. The normalization is assumed by the following equations.

(a) LB (lower-the-better)

$$X_i^*(k) = \frac{\min X_i(k)}{X_i(k)} \quad (1)$$

(b) HB (higher-the-better)

$$X_i^*(k) = \frac{X_i(k)}{\max X_i(k)} \quad (2)$$

(c) NB (nominal-the-best)

$$X_i^*(k) = \frac{\min\{X_i(k), X_{0b}(k)\}}{\max\{X_i(k), X_{0b}(k)\}} \quad (3)$$

Here, i = 1, 2 ...m;

k = 1, 2 ...n

$X_i^*(k)$is the normalized data of the k^{th}element in the i^{th}sequence.

$X_{0b}(k)$is the desired value of the k^{th}quality characteristic. After data normalization, the value of$X_i^*(k)$ will be between 0 and 1. The seriesX_i^*,i=1, 2, 3,........,$m$can be viewed as the comparative sequence used in the grey relationalanalysis.

Step 2: Checking for correlation between two quality characteristics

$Q_i = \{ X_0^*(i), X_1^*(i), X_2^*(i), \ldots\ldots\ldots X_m^*(i) \}$

Let,

Where, i = 1,2,.....n

Shown above is the normalized series of the i^{th}quality characteristic. The correlation coefficient between the two quality characteristics is calculatedusing the following equation:

$$\rho_{jk} = \frac{Cov(Q_j Q_k)}{\sigma_{Q_j}\sigma_{Q_k}} \quad (4)$$

j = 1,2,3....,n

k = 1,2,3....,n

$j \neq k$

Here,$\rho_{jk}$is the correlation coefficient between quality characteristic j and quality characteristic k ; $Cov(Q_j Q_k)$is thecovariance of quality characteristic j and quality characteristic k ;$\sigma_{Q_j}$and $\sigma_{Q_k}$are the standard deviation of qualitycharacteristic j and quality characteristic k , respectively.

The correlation is checked by testing the following hypothesis:

$H_0 : \rho_{jk} = 0$ (There is no correlation)

$H_0 : \rho_{jk} \neq 0$ (There is correlation)

Step 3: Calculation of the principal component score

(a) Calculation of the Eigenvalue$\lambda_k$and the corresponding eigenvectorβ_k (k = 1,2,......n) from the correlation matrixformed by all quality characteristics.

(b) Calculation of the principal component scores of the normalized reference sequence and comparative sequences usingthe equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj} \qquad (5)$$

Where,$Y_i(k)$ is the principal component score of the k^{th}element in the i^{th}series.

$X_i^*(j)$is the normalized value of the j^{th}element in the i^{th}sequence, and$\beta_{kj}$is the j^{th}element of eigenvectorβ_k

(c) The principal component having highest accountability proportion (AP) can be treated as the overall qualityindex which is to be optimized finally. The quality loss$\Delta_{0,i}(k)$ of that index (compared to ideal situation) iscalculated as follows:

(d)

$$\Delta_{0,i}(k) = \begin{cases} |X_0^*(k) - X_i^*(k)| & \textit{No significant correlation between quality characterstics} \\ |Y_0(k) - Y_i(k)| & \textit{Significant correlation between quality characterestics} \end{cases}$$

III. UTILITY CONCEPT

According to the utility theory (Kumar *et al* 2000; Walia *et al* 2006), if *Xi* is the measure of effectiveness of an attribute (or quality characteristics) *i* and there are *n* attributes evaluating the outcome space, then the joint utility function can be expressed as:

$$U(X_1, X_2, \ldots \ldots X_n) = f(U_1(X_1), U_2(X_2), \ldots \ldots, U_n(X_n))$$

Here$U_i(X_i)$is the utility of the i_{th}attribute.

The overall utility function is the sum of individual utilities if the attributes are independent,and is given as follows:

$$U(X_1, X_2, \ldots \ldots X_n) = \sum_{i=1}^{n} U_i(X_i)$$

The attributes may be assigned weights depending on the relative importance or prioritiesof the characteristics. The overall utility function after assigning weights to the attributes canbe expressed as –

$$U(X_1, X_2, \ldots \ldots X_n) = \sum_{i=1}^{n} W_i \cdot U_i(X_i)$$

Here W_i is the weight assigned to the attribute *i*. The sum of the weights for all the attributes should be equal to 1.

A preference scale for each quality characteristic is constructed for determining its utilityvalue. Two arbitrary numerical values (preference number) 0 and 9 are assigned to the justacceptable and the best value of the quality characteristic respectively. On logarithmic scale, the preference numberP_i can be expressed as follows:

$$P_i = A * \log\left(\frac{X_i}{X_i'}\right) \qquad (6)$$

Here X_i is the value of any quality characteristic or attribute *i*,X_i' is just an acceptable value

of quality characteristic or attribute *i*and *A* is a constant. The value *A* can be found using thecondition that if $X_i = X^*$(where X^* is the optimal or the best value), then $P_i = 9$

Therefore,

$$A = \frac{9}{\log \frac{X^*}{X_i'}} \qquad (7)$$

The overall utility can be expressed as follows:

$$U = \sum_{i=1}^{n} W_i \cdot P_i \qquad (8)$$

Subject to the condition:

$$\sum_{i=1}^{n} W_i = 1$$

Among the various quality characteristics types, viz. Lower-the-Better (LB), Higher-the-Better (HB), and Nominal-the-Best (NB) suggested by Taguchi, the utility function would be of theHigher the-Better type. Thereforethe quality characteristics considered for its evaluation will automatically be optimized (maximized or minimized as the case may be) if the quality function is maximized.

In the proposed approach utility values of individual responses are accumulated to calculate overall utility index. Overall utility index serves as the single objective function for optimization.

IV. TAGUCHI METHOD

Taguchi's philosophy, developed by Dr.Genichi Taguchi, is an efficient tool for the design of high quality manufacturing system. Taguchi's Orthogonal Array (OA) provides a set of well-balanced experiments (with less number of experimental runs), and Taguchi's signal-to-noise ratios (S/N), which are logarithmic functions of the desired output, serve as objective functions in the optimization process. The Taguchi method uses a statistical measure of performance called signal-to-noise ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise).The ratio depends on the quality characteristics of the product/process to be optimized.

Taguchi's S/N Ratio for (NB) Nominal-the-best

(Quality characteristics is usually a nominal output, say *Diameter)*

$$\frac{S}{N} = 10log\frac{\bar{y}}{s_y^2} \qquad (9)$$

Taguchi's S/N Ratio for (LB) Lower-the-better

(Quality characteristics is usually a nominal output, say *Defects)*

$$\frac{S}{N} = -10log\frac{1}{n}(\Sigma y^2) \qquad (10)$$

Taguchi's S/N Ratio for (HB) Higher-the-better

(Quality characteristics is usually a nominal output, say *Current)*

$$\frac{S}{N} = -10log\frac{1}{n}(\Sigma\frac{1}{y^2}) \qquad (11)$$

V. EXPERIMENTATION

5.1 Selection of cutting parameters

Surface quality and dimensional accuracy are the two important features of a product in any machining operation. The theoretical surface roughness generally depends on many parameters such as the tool, tool material, work material, machine-tool rigidity and various cutting conditions including feed rate, depth of cut and cutting speed (Boothroyd& Knight 1989; Alauddin*et al* 1995). In anyexperimental study, it is difficult to consider all these factors that affect the surface finish.Available literature reveals that depth of cut, spindle speed and feed rate are the three primary machining parameters and thus these are considered as design factors in the present study.

5.2 Selection of response variables

From literature review it is found that, all the studies, whether experimental or analytical, mostly concentrate on the centre line average roughness value for surface quality. But considerationof only centre line average roughness is not sufficient to describe the surface quality ofa multi scale rough surface (Sahoo 2005). Thus, the intention of the present study is the consideration of thefollowing four roughness parameters as the response variables: centre line average roughness*(Ra)*; root mean square roughness *(Rq)*; kurtosis *(Rku)* and mean line peak spacing *(Rsm)*.

5.3 Work piece material used

The present study was carried out with medium leaded brass UNS C34000. The material properties are available in the material hand book. All the specimens were in the form of 100mm × 75mm × 25mm blocks.

5.4 Cutting tool used

Coated carbide tools have been found to perform better than uncoated carbide tools. Thus, commercially available CVD coated carbide tools have been used in this investigation.

5.5 Design of experiment (DOE)

The Design of Experiment technique allows us to carry out the modelling and analysis of the influence of process variables (design factors) on the response variables. In the present study, depth of cut (*d*, mm), spindle speed (*N*, rpm) and feed rate (*f* , mm/min) have been chosen as design factors while other parameters have been assumed to be constant over the experimental domain.

The process variables (design factors) with their values on different levels are listed in table 1. For each of the factors, five levels having nearly equal spacing, within the operating range of the parameters have been selected. In the present investigation, *L*25 Orthogonal Array (OA) (Peace 1993) design has been considered for experimentation. Interaction effect of process parameters has been assumed negligible.

5.6 Equipments used

The machine used for the milling tests is a 'DYNA V4·5' CNC end milling machine.[8]

Table 1. Different levels of the experiment

Levels	Brass		
	d(mm)	N(rpm)	f(mm/min)
1	0.1	1500	550
2	0.15	1800	600
3	0.2	2100	650
4	0.25	2400	700
5	0.3	2700	750

Table 2. Experimental Results

S. No.	Measured roughness parameters			
	Ra	Rq	Rku	Rsm
1	1.427	1.650	2.070	0.212
2	1.257	1.467	2.000	0.212
3	1.237	1.510	2.470	0.157
4	1.102	1.332	2.370	0.171
5	1.185	1.447	2.250	0.182
6	1.862	2.252	2.880	0.191
7	1.244	1.477	2.250	0.171
8	1.167	1.372	2.100	0.175
9	1.282	1.552	2.200	0.182
10	1.007	1.220	2.570	0.133
11	1.210	1.440	2.450	0.199
12	1.350	1.590	2.330	0.235
13	1.005	1.252	2.860	0.140
14	0.837	1.040	2.850	0.138
15	0.881	1.112	3.350	0.142
16	1.267	1.542	2.580	0.198
17	1.125	1.420	2.950	0.136
18	0.758	0.934	2.600	0.123
19	0.799	0.987	2.610	0.153
20	0.985	1.137	2.040	0.152
21	1.182	1.512	3.140	0.226
22	0.903	1.104	2.580	0.159
23	0.761	0.958	3.010	0.145
24	0.745	0.905	2.480	0.167
25	0.766	0.942	2.860	0.140

The surface roughness parameters have been measured in this experiment using the stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The measured roughness parameters along with the Design matrix have been shown in Table 3.

VI. DATA ANALYSIS

Experimental data have been normalized using equation 2. For surface roughness a Higher the better criterion has been selected. The normalized data have been shown in the table 3.

Table 3. Normalized Data

S. No.	Ra	Rq	Rku	Rsm
Ideal Sequence	1.0000	1.0000	1.0000	1.0000
1	0.5221	0.5485	0.9662	0.5802
2	0.5927	0.6169	1.0000	0.5802
3	0.6023	0.5993	0.8097	0.7834
4	0.6760	0.6794	0.8439	0.7193
5	0.6287	0.6254	0.8889	0.6758
6	0.4001	0.4019	0.6944	0.6440
7	0.5989	0.6127	0.8889	0.7193
8	0.6384	0.6596	0.9524	0.7029
9	0.5811	0.5831	0.9091	0.6758
10	0.7398	0.7418	0.7782	0.9248
11	0.6157	0.6285	0.8163	0.6181
12	0.5519	0.5692	0.8584	0.5234
13	0.7413	0.7228	0.6993	0.8786
14	0.8901	0.8702	0.7018	0.8913
15	0.8456	0.8138	0.5970	0.8662
16	0.5880	0.5869	0.7752	0.6212
17	0.6622	0.6373	0.6780	0.9044
18	0.9828	0.9690	0.7692	1.0000
19	0.9324	0.9169	0.7663	0.8039
20	0.7563	0.7960	0.9804	0.8092
21	0.6303	0.5985	0.6369	0.5442
22	0.8250	0.8197	0.7752	0.7736
23	0.9790	0.9447	0.6645	0.8483
24	1.0000	1.0000	0.8065	0.7365
25	0.9726	0.9607	0.6993	0.8786

After normalization a check has been made to verify whether the responses i.e. the quality indices are correlated or not. The correlation coefficient between the different surface roughness characteristics have been verified and are found to be non zero values hence all the responses are proven to be correlated.

Table 4. Eigen Values and Eigen Vectors

Eigen Value	2.699	0.901	0.398	0.002
AP	0.675	0.225	0.100	0.000
CAP	0.675	0.900	1.000	1.000

VARIABLE	PC1	PC2	PC3	PC4
Ra	0.583	-0.215	0.321	0.715
Rq	0.569	-0.314	0.308	-0.695
Rku	-0.278	-0.920	-0.266	0.070
Rsm	0.510	0.093	-0.855	-0.004

Table 5. Principal Components

Major Principal Components			
S.No.	MAJOR PRINCIPAL COMPONENTS		
	ψ1	ψ2	ψ3
Ideal sequence	1.3840	-1.3560	-0.4920
1	0.6438	-1.1194	-0.4165
2	0.7144	-1.1872	-0.3818
3	0.8666	-0.9898	-0.5073
4	0.9130	-1.0682	-0.4132
5	0.8200	-1.0865	-0.4198
6	0.5973	-0.7912	-0.4831
7	0.8175	-1.0720	-0.4705
8	0.8412	-1.1552	-0.4462
9	0.7625	-1.0816	-0.4535
10	1.1087	-1.0219	-0.5318
11	0.8048	-1.0233	-0.3544
12	0.6739	-1.0384	-0.3234
13	1.0971	-0.9480	-0.4766
14	1.2735	-1.0273	-0.3950
15	1.2319	-0.9061	-0.3773
16	0.7781	-0.9661	-0.3678
17	1.0215	-0.8821	-0.5447
18	1.4205	-1.1303	-0.4457
19	1.2623	-1.1186	-0.3095
20	1.0340	-1.2392	-0.4647
21	0.8085	-0.8588	-0.2481
22	1.1265	-1.0760	-0.3503
23	1.3562	-1.0395	-0.2968
24	1.3034	-1.2024	-0.2152
25	1.3673	-1.0724	-0.3291

In order to eliminate response correlations Principal Component Analysis has been applied to derive four independent quality indices called principal components. The analysis of the correlation matrix has been shown in the table. The independent quality indices are denoted as PC1, PC2, PC3 and PC4. Table 5 represents the values of these independent principal components for 25 experimental runs. The principal components are calculated using the equation 5.

It has been found that the cumulative accountability proportion for the first three components, by itself is 100%. Therefore the third component can be eliminated and the first three components have been taken into further consideration. Quality loss values have been calculated and the values are are shown in table 6.

Table 6. Quality loss estimates

Quality loss estimates			
sl. No.	quality loss estimates		
	ψ1	ψ2	ψ3
1	0.7402	0.2366	0.0755
2	0.6696	0.1688	0.1102
3	0.5174	0.3662	0.0153
4	0.4710	0.2878	0.0788
5	0.5640	0.2695	0.0722
6	0.7867	0.5648	0.0089
7	0.5665	0.2840	0.0215
8	0.5428	0.2008	0.0458
9	0.6215	0.2744	0.0385
10	0.2753	0.3341	0.0398
11	0.5792	0.3327	0.1376
12	0.7101	0.3176	0.1686
13	0.2869	0.4080	0.0154
14	0.1105	0.3287	0.0970
15	0.1521	0.4499	0.1147
16	0.6059	0.3899	0.1242
17	0.3625	0.4739	0.0527
18	0.0365	0.2257	0.0463
19	0.1217	0.2374	0.1825
20	0.3500	0.1168	0.0273
21	0.5755	0.4972	0.2439
22	0.2575	0.2800	0.1417
23	0.0278	0.3165	0.1952
24	0.0806	0.1536	0.2768
25	0.0167	0.2836	0.1629

The utility values are calculated using equation 7 and they are shown in table 7. The three values of the constants that are used for calculating the utility values are found as **A1= -5.736 A2 = -13.146, A3 = -6.026.**

Table 7. Utility Values

Sl. No.	utility values		
	ψ1	ψ2	ψ3
1	0.1421	4.9675	3.4013
2	0.3765	6.8945	2.4101
3	0.9784	2.4730	7.5770
4	1.1977	3.8484	3.2877
5	0.7769	4.2238	3.5178
6	0.0000	0.0000	9.0000
7	0.7668	3.9257	6.6853
8	0.8665	5.9041	4.7073
9	0.5505	4.1203	5.1628
10	2.4518	2.9980	5.0780
11	0.7151	3.0206	1.8288
12	0.2392	3.2865	1.2968
13	2.3556	1.8566	7.5607
14	4.5839	3.0910	2.7438
15	3.8367	1.2979	2.3050
16	0.6096	2.1158	2.0975
17	1.8091	1.0019	4.3385
18	7.1703	5.2356	4.6786
19	4.3577	4.9482	1.0893
20	1.8911	9.0000	6.0638
21	0.7300	0.7280	0.3306
22	2.6073	4.0063	1.7520
23	7.8025	3.3066	0.9138
24	5.3209	7.4354	0.0000
25	9.0000	3.9335	1.3869

From the utility values, the utility index has been found out using Equation 6 and Equation 8. Corresponding S/N ratios for the utility index values have been calculated. These values are shown in Table 8. In this computation it has been assumed that all quality indices are equally important and hence same priority weightage of 33.33% is taken. Figure represents the S/N ratio plot for overall utility index. S/N ratio is calculated using the Taguchi higher the better equation 11.

Table 8. Utility Index and S/N ratio

S. No	Utility index	S/N ratio
1	2.8086	8.9699
2	3.1947	10.0887
3	3.6394	11.2205
4	2.7502	8.7871
5	2.8111	8.9775
6	2.9700	9.4551
7	3.7547	11.4915
8	3.7877	11.5676
9	3.2451	10.2245
10	3.4742	10.8170
11	1.8363	5.2789
12	1.5914	4.0358
13	3.8851	11.7879
14	3.4382	10.7265
15	2.4551	7.8013
16	1.5916	4.0365
17	2.3594	7.4559
18	5.6379	15.0224
19	3.4304	10.7069
20	5.5951	14.9562
21	0.5903	-4.5793
22	2.7606	8.8202
23	3.9676	11.9705
24	4.2096	12.4848
25	4.7257	13.4894

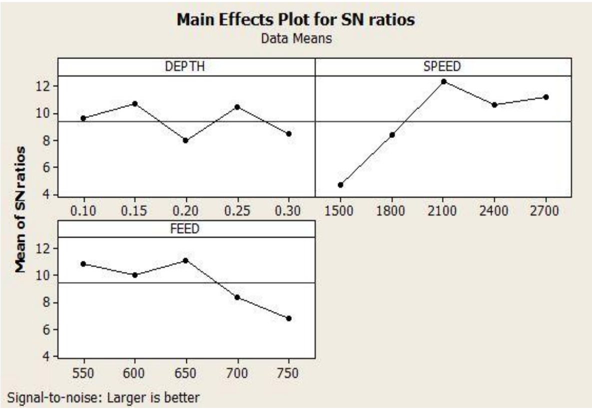

Fig. 1 : S/N Ratio plot

Optimal parameter setting has been evaluated from figure 1. The optimal setting should confirm the highest utility index. The predicted optimal setting becomes Depth = 0.15mm, Speed = 2100 rpm, Feed = 650mm/min.

After evaluating the optimal parameter setting, the next step is to predict and verify the optimal result using the confirmatory test. The predicted S/N ratio is found out as 15.2639 and the corresponding utility index is found out as 5.8797. Hence by working at the predicted readings the maximum efficiency in machining is obtained.

VII. CONCLUSION

All studies reported in literature mostly concentrate on the centre line average roughness *Ra* value for surface quality. It is felt that consideration of centre line average roughness by itself is not sufficient to describe surface quality. The other roughness parameters like root mean square roughness *(Rq)*, kurtosis *(Rku)* and mean line peak spacing *(Rsm)* should be taken into account and should be included in the analysis.

Hence this study has effectively combined Principal component analysis and the Utility theory in order to optimize the milling operation. The following conclusions may be drawn from the results of the experiments –

1) Application of PCA has been recommended to eliminate response correlation by converting correlated responses into uncorrelated quality indices called principal components which have been as treated as response variables for optimization.
2) Based on accountability proportion (AP) and cumulative accountability proportion (CAP), PCA analysis can reduce the number of response variables to be taken under consideration for optimization purposes. This is really useful in situations where a large number of responses have to be optimized simultaneously.
3) Utility based Taguchi method has been found rewarding for evaluating the optimum parameter setting and solving such a multi-objective optimization problem.
4) The aforesaid approach can be recommended for continuous quality improvement and off-line quality control of a process/product.

VIII. REFERENCES

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